

Quantifying the distribution of editorial power and manuscript decision bias at the mega-journal PLOS ONE

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Abstract

We analyzed the longitudinal activity of nearly 7,000 editors at the mega-journal PLOS ONE over the 10-year period 2006-2015. Using the article-editor associations, we develop editor-specific measures of power, activity, article acceptance time, citation impact, and editorial remuneration (an analogue to self-citation). We observe remarkably high levels of power inequality among the PLOS ONE editors, with the top-10 editors responsible for 3,366 articles – corresponding to 2.4% of the 141,986 articles we analyzed; the Gini-index of this power distribution is 0.583, which is comparable to some of the highest wealth-inequalities in the world. Such high inequality levels suggest the presence of unintended incentives, which may reinforce unethical behavior in the form of decision-level biases at the editorial level. Due to the size and complexity associated with managing such a large mega-journal, our results indicate that editors may become apathetic in judging the quality of articles and susceptible to modes of power-driven misconduct. We used the longitudinal dimension of editor activity to develop two panel regression models which test and verify the presence of editor-level bias. In both models we clustered the articles within each editor's profile and used editor fixed-effects to isolate the individual-level trends over time: in the first model we analyzed the citation impact of articles, and in the second model we modeled the decision time between an article being submitted and ultimately accepted by the editor. We focused on two variables that represent social factors that capture potential conflicts-of-interest: (i) we accounted for the social ties between editors and authors by developing a measure of repeat authorship among an editor's article set, and (ii) we accounted for the rate of citations directed towards the editor's own publications in the reference list of each article he/she oversaw. Our results indicate that these two factors play a significant role in the editorial decision process, pointing to the misuse of power. Moreover, these two effects appear to increase with editor age, which is consistent with behavioral studies concerning the evolution of misbehavior and response to temptation in power-driven environments. And finally, we analyze “editor remuneration” – the number of citations one might receive by adapting biases towards certain scientific peers as well as self-citations from scientific strangers. By applying quantitative evaluation to the gatekeepers of scientific knowledge, we shed light on various issues crucial to science policy, and in particular, the management of large megajournals.

Keywords: Mega-journal, Power inequality, Review process, Editorial service, Science of science, Journal management

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1. Introduction

The emergence and rapid growth of megajournals in the last decade (Solomon and Bjork, 2012; Binfield, 2013; Solomon, 2014; Bjork, 2015) represents a drastic industrial paradigm shift in the production of scientific knowledge. This paradigm shift places pressure on several fundamental aspects of the scientific endeavor. First, in addition to the pay-to-publish model, the personnel resources required to referee the 50,000+ megajournal articles each year is quite substantial (Binfield, 2013). Second, the publication of these articles also stresses the individual cognitive capacity of scientists as well as the technological knowledge-storing capacity which is fundamental to the long-term need to be able to search, retrieve, and classify knowledge. For example, over its first 6 years, PLOS ONE grew at an annual rate of 58%, roughly 18 times larger than the net growth rate of scientific publication over the last half-century; in 2012, the 23,468 articles published in PLoS ONE represented approximately 0.1% of science publications indexed by Thomson Reuter’s Science Citation Index (Pan et al., 2016). And third, megajournals have initiated a completely different model of managing the scientific publication process. In particular, PLOS ONE relies on thousands of acting scientists who comprise its editorial board, who simultaneously continue their role as research leaders. This dichotomy clearly establishes the conditions for conflicts-of-interest, whereby scientists must balance conflicting incentives arising from their distinct duties as authors and editors.

As such, megajournals may be particularly susceptible to misconduct – by authors and journal editors – because oversight and careful monitoring of individual activities is truly challenging in such a large and complex socio-economic system. This is, to some extent, supported by the lack of transparency in the review process, which has traditionally involved single or double blinds for the authors and reviewers, and also for the editors whose identity is oftentimes unknown even after the article is published.¹ Particular to the review process of science, which is ironically obscured to protect the process itself, it is not difficult to imagine that misconduct may organically arise from the basic pursuit of internal (and external) power (Malhotra and Gino, 2011) and the innate difficulty of avoiding temptation in decision-heavy endeavors (Gino et al., 2011). As such, given the history of misconduct in science combined with the relative ease in which information can be collected and made publicly available, it is important to develop transparent methods to quantitatively monitor the activities of both authors and editors, so to ensure the integrity of the scientific process.

Here we provide an in-depth analysis of the largest journal in the world, PLOS ONE, focusing on editorial power and identifying the role of social factors in their decision processes. To achieve this, we analyzed the entire article history over the 10-year period 2006-2015. By combining editor, author, article and citation level data for each publication, we constructed a large multi-variable longitudinal database centered around the 6,934 PLOS ONE editors. We use this data to provide descriptive and

¹However, unlike most journals, PLOS ONE provides the name of the editor overseeing each article, a crucial aspect which we leverage in this study.

panel regression analyses, which foster insight into a domain of science that has traditionally been undocumented since most journals do not make clear the editor-article association within the article. As such, to the best of our knowledge, this is the first study to develop editor-level measures for quantitatively evaluating an editor’s history of editorial service. Moreover, these methods are the starting point for measuring individual and population-level shifts in editorial behavior over time.

The general hypothesis that we test in this work is whether bias exists in the editorial process. Identifying, with certainty, cases of scientific misconduct on the part of editors would require case-by-case investigation which is beyond the capacity of our data and methods. Thus, we refrain from orientating our study on particular editors, instead focusing on aggregate patterns that nevertheless indicate that editorial behaviors shift over time as they gain power and, as a result, reach the limits of their temporal and cognitive capacity to pay close attention to each article they oversee. This point is particularly important in the context of large megajournals, which are typically electronic online-only and based on a pay-to-publish model, meaning that the production process is primed for steady, and possibly overwhelming, growth. Moreover, research indicates that when the acceptability of misconduct increases gradually, that a “slippery-slope effect” (Gino and Bazerman, 2009) may emerge, and the spread of misconduct may be inevitable even among individuals who initially had good intentions. It is likely that scientific actors are susceptible to such forces, because the information concerning the review process is tightly concealed. Ironically, instead of protecting the system, this lack of transparency may harbor the emergence of author and editor-level strategies for “gaming the scientific system”. Given the increasing role of citation-based evaluation – of researchers and journals – it is entirely possible that misconduct may straddle both sides of the table.

In order to provide light on this issue, we develop methods to quantitatively measure the author-editor relationship. In particular, we investigate two types of cooperative social “back-scratching”: (i) editors making biased decisions in the review process towards their close scientific peers, and (ii) authors enticing favorable decisions by providing remuneration in the form of citations directed to the editor’s research. We leverage the longitudinal aspects of editorial profiles to demonstrate for these two effects that, indeed, there are statistically significant trends in editor behavior at PLOS ONE that are consistent with power-driven bias and remuneration incentives.

2. Literature review

This work contributes to several research streams focused on understanding the economics of science (Stephan, 2012), the growth of scientific production (Pan et al., 2016), and ethics issues arising from this growth paradigm (Petersen et al., 2014). Our work also draws on the scientific community’s efforts to develop data-driven models for the social processes underlying science (Scharnhorst et al., 2012; Börner et al., 2016). To this end, we employ a data-driven approach that leverages the vast amounts of available publication metadata to expand our knowledge about science itself (Evans and Foster, 2011). In particular, our effort to capture the obscure yet fundamental interactions between individuals – here the editor-author relation – which builds on concepts and methods from social

science is only possible due to recent simultaneous advances in computing, online data availability (Lazer et al., 2009).

As science continues to expand, it is important to frame introspective ‘science of science’ analysis around important questions of science policy (Fealing and eds., 2011; Stephan, 2012; Börner et al., 2016) – e.g. how to increase the efficiency of scientific discovery (Rzhetsky et al., 2015) and improve the evaluation and sustainability of scientific careers in an increasingly metrics-oriented system (Wilsdon et al., 2015). Indeed, scientists should be developing ideas to improve the publication system to the same degree that they are rethinking the scientific funding system (Bollen et al., 2016). If not, it is possible that the system may become susceptible growth of inequality (Xie, 2014; Petersen and Penner, 2014), corruption, and unintended consequences arising from lack of oversight, which are common flaws of complex human-oriented systems. In addition to these prominent flaws, the scientific process is also characterized by subtle innate biases – such as the editorial and peer review bias in the reporting of positive scientific results, as apposed to null results (Kravitz et al., 2010)

This study also provides a timely quantitative insight of the largest among the rapidly growing ecosystem of megajournals, which feature journals that are publisher, society, and research-area specific, such as Heliyon (Elsevier), Springer Plus (Springer), Scientific Reports (Nature), Royal Society Open Sciences, IEEE Access, PeerJ, SAGE Open (Solomon and Bjork, 2012; Binfield, 2013; Solomon, 2014; Bjork, 2015). And finally, our analysis also contributes to recent research on manuscript decision timescales (Powell, 2016; Sugimoto et al., 2013) by identifying social factors that can explain the wide range in acceptance times.

3. Data and Methodology

3.1. PLOS ONE article data

We gathered the citation information for all PLOS ONE publications from the Thomson Reuters Web of Science (TRWOS) Core Collection. From this data we obtained a master list of the unique digital object identifier, DOI_A , as well as the number of authors, k_A , a list of their surnames and first-middle name initials, and the number of citations, c_A , at the time of the data download (census) date on December 3, 2016.

We then used each DOI_A to access the corresponding online XML version of each article at PLOS ONE by visiting the unique web address given by each “http://journals.plos.org/plosone/article?id=” + “ DOI_A ” string combination.

3.2. Article and editor measures

In our study, the principal unit of analysis is a PLOS ONE editor, which we denote by the index E . Thus, for each E we collected the corresponding group of N_E articles over which he/she has served as editor. This Editor-Article association is publicly available in both the published electronic article as well as on the article webpage, appearing in the article abstract and author information byline. To maintain context among the variables we define in our analysis, quantities that are mostly

article-specific are denoted by the index A , those that are mostly editor specific are denoted by the index E , and quantities that are properties of both are indexed as $x_{A,E}$.

Embedded in the XML file for each article are various editor, coauthor, and article metadata which we extracted from the webpage of each A and then aggregated for each E . All together, the entire database for the 10-year period 2006-2015 is comprised of 141,986 articles and 6,934 editors. In both of our panel regression models, we refine this dataset to the 3749 editors with $N_E \geq 10$ articles to reduce small sample noise at the editor level, resulting in 128,734 articles. From these articles and their editors we define the following quantities:

1. The net editorial activity, N_E , is the number of articles overseen by editor E over the total editor service period, L_E , which is the number of days between an editor's first and last article – through the end of 2015.
2. The article acceptance time, Δ_A , is the number of days between the submission and acceptance of article A . Note that this duration does not include the time interval between acceptance and publication, as factors external to the editorial process could affect this process, its timeline, and thus its ultimate duration.
3. The editorial turnover time, $d_E = L_E/N_E$, is the mean number of days between two articles overseen by editor E published in PLOS ONE.
4. The editorial mean acceptance time, Δ_E , is the mean Δ_A , which is calculated within his/her article group. Likewise, we measured the variability in Δ_A using the coefficient of variation, $cov_E = \sigma_E[\Delta_A]/\Delta_E$, calculated within each editor's article subset (where $\sigma[\dots]$ denotes the standard deviation); see Fig. S2(A).
5. The “citation remuneration” C_A is the total number of references that cite the editor's research among the articles he/she edited. This number is calculated by going through the reference list of each article, and identifying publications that include the editor's last name and first-name initial among the authors. Likewise, the editor citation rate, f_A , is the fraction of the total references on a given article that cite his/her work.
6. The editor's PLOS ONE service age, $\tau \equiv \tau_{A,E}$, is the time difference between the acceptance date of the first accepted article of editor E and the acceptance date of the acceptance date of article A , measured in years.

Figure 1 shows the probability distribution for several of these important quantities, with article-level statistics shown in blue, and editorial-level statistics shown in red throughout the remainder of the analysis.

3.3. Article subject area classification

It is well known that citation rates are affected by discipline-dependent factors. Indeed PLOS ONE is comprised of articles from a range of disciplines, and is classified by TRWOS as a “Multidisciplinary”

journal. Thus, we were careful not to blindly pool the citation impact measures from all articles together. Instead, we methodically separated the articles into subsets, so that the relative citation difference between two articles less biased by (sub)disciplinary factors such as research community size and innovativeness, but rather, is an estimate of differences in research quality and scientific impact.

We grouped the articles into 6 refined core subject areas (SA) based on the internal PLOS ONE classification [subject area classification system](#) derived from a controlled thesaurus of more than 10,000 keywords. To be specific, we started with the keywords appearing on the webpage of article *A*. Nearly all articles have 8 keywords per article, with only a handful of articles containing less than 8. PLOS ONE also has an article-classification scheme which is used to group articles for comparing article visibility. The 2-level classifications are accessible in the “page-views” applet on each article’s “Metrics” page, for example the article with DOI 10.1371/journal.pone.0000112 is classified primarily as “Biology and life sciences”, with 3 subclassifications (Evolutionary Biology, Genetics, and Population Biology). In all, the 10 top-level classifications are: (i) Biology and life sciences, (ii) Medicine and health sciences, (iii) Physical sciences, (iv) People and places, (v) Social sciences, (vi) Engineering and technology, (vii) Computer and information sciences, (viii) Ecology and environmental sciences, (ix) Earth sciences, (x) Science policy. We collected these top-level classifications from each article’s “Metrics” page, and are ordered here according to their frequency among PLOS ONE articles.

We then used the statistics of the bipartite association between keywords and top-level classifications on each article to establish a vector of weights corresponding to the 10 top-level PLOS ONE classifications in such a way that we could more precisely identify an article with a single classification. More specifically, for each article, we identified the principal SA as the one for which the individual keywords contributed the most weight. Take again the article DOI:10.1371/journal.pone.0000112 with the 8 keywords “Chromosome 4”, “Genetic loci”, “Centromeres”, “X chromosomes”, “Population genetics”, “Chromosomes”, “Sex chromosomes”, “Alleles”. As one might expect, these article keywords give the largest weight to SAs (i) “Biology and life sciences” and (ii) “Medicine and health sciences”.

Applying this method to all articles, we found that the most common first and second ranked classification across all PLOS ONE articles are indeed (i) and (ii). Figure [S1\(A\)](#) shows the SA count histogram for all PLOS ONE articles, with 123,750 (87.1% of all articles) having “Biology and life sciences” as the principal classification, and none having “Science policy” as the principal classification. Contrariwise, only 17 articles had “Earth sciences” as the principal classification. To account for the fact that the majority of the keywords in the PLOS ONE thesaurus are related to (i) and (ii), leading to the disparity in the principal classification, we created an exception rule in order to better account for the second-ranked classification. First, if the principal classification was (i), then we instead used the second-ranked classification as the principle classification. This rule helped to classify more publications for SA (iii)-(ix), as demonstrated by the second count histogram shown in Fig. [S1\(B\)](#). As one final step to condense the SA classifications, we joined the groups (iv) and (v), (vi) and (vii), and (viii) and (ix), since there is considerable overlap between these classification groups. Thus, Fig. [S1\(C\)](#) shows the final refined distribution of articles across the 6 refined SA used in our analysis: the smallest refined SA is 6/7 with 533 articles and the second-smallest is 4/5 with

1839 articles over 2006-2015; the remaining refined SA are comprised of 8000 or more articles over the 10-year period. In what follows, we define the variable $s = 1...6$ as an index for these refined SA; we use s as a subset index in defining normalized citations and dummy variables in our regression analysis.

3.4. Normalization of citation counts to account for citation inflation and SA-level factors

Comparing the raw citation counts of articles from different years t and disciplines s is a common challenge in science of science research. This difficulty arises due to three principal statistical biases: variation in publication rates across discipline, censoring bias and citation inflation. The first refers to the fact that larger disciplines, e.g. Biology and life sciences, produce more publications, and hence, more citations than smaller disciplines such as Earth sciences. The second bias refers to the fact that older publications have had more time to accrue citations than newer ones. And the third bias refers to the fact that more citations are produced over time as a product of increasing publication rates and reference list lengths, leading to a significant inflation in the relative value of citations. By way of example, a recent study demonstrated that the total number of references produced by all scientific articles is growing by 5.6% annually, and hence doubling every 12.4 years (Pan et al., 2016).

To address these three measurement problems, we map the raw citation count $c_{A,t}^s$ of a given article – measured at the TRWOS census date $Y = 12/03/2016$ – to a normalized value

$$z_A^s \equiv \frac{\ln(1 + c_{A,t}^s) - \langle \ln(1 + c_t^s) \rangle}{\sigma[\ln(1 + c_t^s)]}, \quad (1)$$

where the mean, $\langle \ln(1 + c_t^s) \rangle$, and the standard deviation, $\sigma[\ln(1 + c_t^s)]$, are calculated only over publications from the same year t and refined subject area s . The constant 1 is added to each citation count in order to avoid the problem of uncited articles and does not affect the results.

By analyzing the logarithm of the citation count, this normalization leverages the universal log-normal statistics of citation distributions (Radicchi et al., 2008). Moreover, by rescaling the logarithm by the standard deviation, the underlying inflationary bias has been removed from z , i.e. detrended so to permit cross-era comparison. As such, z is particularly well-suited for regression analysis, as recently demonstrated in longitudinal analyses of cumulative advantage (Petersen and Penner, 2014) and collaboration (Petersen, 2015) within researcher careers. Figure S1(B) confirms that the probability distributions $P(z|s, t)$ are all approximately normally distributed, and thus sufficiently time invariant for the purposes of our analysis, for each subject area and year – with the exception of 2015 publications, which we omit from our first regression analysis where z is the dependent variable.

3.5. Repeat authors

In order to investigate the impact of social ties on editorial decision processes, we analyzed the set of N_k authors appearing within the article set of a given editor. That is, for each article we recorded the last name and first initial of each of the k_A coauthors and tallied the number of articles $A_{E,k}$ for a given surname + first-initial combination – for each editor. Because of the name disambiguation problem, it is difficult to distinguish authors with the same name, especially for authors with extremely

common surnames. Thus, we removed from our analysis those authors with common surnames (e.g. Xie, Yang, Adams, Johnson), using the Editor name list to determine which surnames appear with significant frequency that might significantly contribute to false-positive union of coauthor counts. We describe this procedure in the Supplementary Information Section S1.1, where we also provide the full list of surnames which we ignored in our analysis.

After tallying the author names for each E we obtained a ranked list of those coauthors. We investigated the distribution of the rank-coauthor profile within an editor’s article set, and found that the distribution $P(A_{E,k})$ decays quasi-binomially, but with deviations in the tail. Also, as expected, the maximum value $\text{Max}[A_{E,k}]$ depends to a large degree on N_E . Thus, unlike the rank-coauthor distribution within a given researcher’s publication profile, which is well-fit by a discrete exponential distribution and characterized by a subset of “super-ties” representing extremely strong collaboration partners (Petersen, 2015), the editor-author distribution is not characterized by such obviously strong social ties.

Nevertheless, since the purpose of this method is to identify a set of articles which may have been influenced by external social ties with the editor, the “repeat coauthor” criteria we converged upon leverages the fact that many top authors within an editor set tend to publish together. As such, we found that the best method for identifying a reasonably-sized subset of articles with repeat ties was to merely tag the authors with 2 or more articles within a given editor’s article set – i.e. repeat authors.

Applying this method, we counted the number of repeat authors per editor, $K2_E$, and we then tagged each of the articles including those authors using the indicator variable $R_{A,E} = 1$. As such, the articles with $R_{A,E} = 1$ represent 13.9% of all articles. Figure S2(B) shows that, within editor profiles, each editor has on average 5.2 repeat authors. Likewise, on a per-article basis, Fig. S2(C) shows that on average 11% of an editor’s articles have $R_{A,E} = 1$ (the median value per editor is 0.1), however the distribution of this fraction ρ_E is skewed with 10% of editors having 26% or more of their articles with $R_{A,E} = 1$. In all, this “repeat author” method identifies a sufficiently large number of articles with $R_{A,E} = 1$ (the rest having indicator value $R_{A,E} = 0$), such that in the following sections we can use this binary classification to identify and quantify possible obscure social factors that may reasonably affect editorial decision processes.

4. Results

4.1. Editorial power distribution

Our analysis reveals an extremely wide range of editorial power that exists within a single journal. For example, ranking editors by N_E , Fig. 1(A) shows the top-100 editors, who collectively oversaw 12.2% of the total 141,986 articles over the 10-year period since the inception of the journal. Moreover, the distribution P_{N_A} calculated across all editors is extremely right-skewed, showing that most editors have served on just a few articles, 50% have served on 11 or less articles, while the top editor Vladimir Uversky has served on roughly 27 times (557/20.5) as many articles as the average editor.

To further demonstrate this power inequality, the Lorenz curve in Fig. 1(C) shows the cumulative fraction of all articles edited by a given percentile: the bottom 25% of editors oversaw just 3% of the

total 141,986 articles; the middle 65% of editors oversaw 55%; the top 10% of editors (693 editors) oversaw 42%; the top-10 editors oversaw 2.4% of the total articles. The Gini-index, representing the area between the Lorenz curve and the diagonal line, is relatively high, comparable to some of the highest wealth inequalities in the world, e.g. in Honduras.

4.2. Editorial activity distribution

The activity of editors is right-skewed, which is partially attributable to the skew in the distribution of acceptance times $P(\Delta_A)$. Figure 1(E) shows that the mean time between articles accepted is on average roughly 55 days, about half as long as the mean Δ_A . This would suggest that most editors are handling roughly two articles at a time, which is not unreasonable. Moreover, comparing panels 1(D,F), the distribution $P(\Delta_E)$ of the mean number of days to accept an article after it was received within an editor’s article subset is comparable in mean – but not standard deviation – to the article-level distribution. One might assume that this variation is purely related to N_E , however the color coding of editors in Figure 1(A) by their individual Δ_E values indicates that among the top-100 editors there is an extremely wide range of accepted article turnover levels. It appears as though the extremely high volume of articles overseen by the top-10 editors is partially due to their fastest acceptance times, with several averaging just around 2 months per article.

4.3. Panel data regressions with observations clustered on Editor profiles

In what follows, we aim to explain the variation in two types of outcomes – the article’s scientific impact and its speed through the review process – using editor and article-level control variables. Of principal interest among the covariates are those representing social aspects of the editorial review process. Namely, we shall focus on the variation due to repeat authors, as indicated by the binary variable $R_{A,E}$. Moreover, we shall also focus on potential evidence of editor remuneration using the rate of references directed at the editor’s publications, f_A . For example, Fig. 1(G) shows the distribution $P(f_A)$, which indicates that 92% of articles do not have any references that cite the editor’s work. Nevertheless, among the remaining 8% of articles with $f_A > 0$, there is a wide range, with the average value $\langle f_A | f > 0 \rangle = 0.036$ corresponding to roughly one in every 30 references citing the editor’s work. And finally, the longitudinal component is rather important, as variation across each editor’s service, captured by τ_E , may indicate shifts in behavior reflecting increased workload, apathy, and possibly even new variations of scientific misconduct.

4.3.1. Model I: Article citation impact, z_A

In this first model, we ask the question: does the scientific quality of the article’s overseen by a given editor change over time? If so, what are the possible explanations? Indeed, similar approaches have been used to demonstrate that within researcher profiles, indeed there is a negative trend in the scientific impact of a researcher’s publications the further on in his/her career (Petersen and Penner, 2014; Petersen, 2015) with various potential individual and social mechanisms that may be responsible for this observed trend.

Thus, the dependent variable is the normalized citation impact of an article z_A^s in subject area s . By matching each article to its editor E , we capture the longitudinal dimension quantified by τ , the number of years into his/her editorship at PLOS ONE. Thus, by sequencing the A by τ , we are able to use a panel regression framework including editor fixed-effects ($\beta_{i,0}$) to control for time-invariant individual-level characteristics. Thus, this model appropriately captures within-career trends. For this panel analysis we exclude articles from 2015, since our analysis of z_A^s in the bottom row of Fig. S1(B) indicates that these articles have not had enough time to sufficiently converged to the baseline Normal $N(0, 1)$ distribution. Thus, by considering only those editors with $N_A \geq 10$, this additional threshold reduces the dataset from 128,734 to 102,741 articles (observations).

The specification of our linear fixed-effects model is given by

$$z_A^s = \beta_{E,0} + \beta_k \ln k_A + \beta_\Delta \ln \Delta_A + \beta_\tau \ln \tau_{A,E} + \beta_R R_{A,E} + D_s + D_t + \epsilon_{A,E} . \quad (2)$$

The results of this basic model estimates are shown in the first two columns of Table 1, where the second column corresponds to the standardized (beta coefficient) coefficients

The article-level variable k_A controls for team-size effects, and is incorporated in logarithm since the distribution of authors per publication is right-skewed and approximately log-normal in various team-oriented disciplines (Petersen et al., 2014). Along these lines, we also include subject area as well as publication year dummies variables to further control for cross-disciplinary and temporal variation in the explanatory variables.

The first covariate of interest is Δ_A , the amount of time it took for the article to be accepted. The model indicates that publications that are under review for a longer time tend to have lower citation impact ($\beta_\Delta < 0; p < 0.000$). This is consistent with the assumption that articles that fail to signal their novelty and/or scientific contribution may require more deliberation time between the authors, the reviewers, and the editor.

The principal explanatory variable of interest, τ_E , the duration of editorial service at PLOS ONE at the time of acceptance of the article, was the strongest variable in explaining z_E , with standardized coefficient $\hat{\beta}_\tau = -0.143$ ($p < 0.000$). This result is consistent with two other studies of longitudinal citation patterns within careers (Petersen and Penner, 2014; Petersen, 2015), and suggests that editorial behavior may shift across his/her career.

We also incorporated the repeat author indicator $R_{A,E}$, which has a significant positive coefficient $\beta_R > 0$, possibly due to the fact that repeat coauthors are likely to be more experienced and more prominent within their scientific community. In order to identify additional signatures of editorial bias, we estimated two additional models, the first including an additional interaction term $R_{A,E} \times \ln \tau_E$ and the second including an additional triple-interaction term $T_{10,E} \times R_{A,E} \times \ln \tau_E$, where $T_{10,E} = 1$ if the editor is ranked in the top-10 according to N_E and 0 otherwise. The former double-interaction term captures the potential combined effect of editor age and social ties while the latter triple-interaction term captures the additional effect of being extremely prominent editor at PLOS ONE. The model estimates for the triple-interaction are shown in the fourth column of Table 1, and indicate that

articles with $R_{A,E} = 1$ have decreasing impact for larger τ ($\beta_{T \times \ln \tau} = -0.025$; $p=0.028$). Moreover, we observe an additional negative effect related to the combination of top-10 editors who accept articles with $R_{A,E} = 1$ for larger τ ($\beta_{T \times R \times \ln \tau} = -0.103$; $p=0.017$).

Figure 2(A) captures the marginal effect of editor service age τ on z_A for the two scenarios for $R_{A,E} = 0, 1$. Indeed, both trends are negative, however the marginal effect for $R_{A,E} = 1$ is even more negative such that by $\ln \tau = 1$, corresponding to roughly 3 years of service, the characteristic article citation impact is below average with no significant difference from the articles with $R_{A,E} = 0$.

4.3.2. Model II: Article acceptance time, Δ_E

The average PLOS One article takes 126 days from being officially received and processed by the editor, reviewed (possibly over several rounds), and finally accepted. This characteristic timescale is higher than the global average which was recently estimated to be roughly 100 days, with only slight variations across journals when disaggregated by impact factors (Powell, 2016). However, there is great variation in the acceptance time Δ_A , demonstrated by the distribution $P(\Delta_A)$ in Fig. 1(D). This variation is highlighted by two remarkable extremes – we observed one publication with $\Delta_A = 0$ (DOI:10.1371/journal.pone.0031292) and one publication (DOI:10.1371/journal.pone.0028904) with $\Delta_A = 1927$ days – taking more than 5 years to finally be accepted! Moreover, we find that 0.43% of articles are received and accepted within 7 days.

Thus, in this second model, we ask the question: what factors may explain the wide range of acceptance times observed across all articles and even within the profiles of individual editors? Can we interpret the results in terms of the remuneration expectations for editorial service? The short preemptive answer is ‘Yes’ – in the next section we shall further illustrate the significant magnitude of remuneration an editor might be able to achieve according to unintended incentives in science aligned with the pursuit of individual citation prestige.

For this panel analysis we use data for editors with $N_A \geq 10$, corresponding to 128,734 articles (observations). The specification of our linear fixed-effects model is given by

$$\ln \Delta_A = \beta_{E,0} + \beta_z \ln z_A + \beta_k \ln k_A + \beta_f f_A + \beta_\tau \ln \tau_{A,E} + \beta_R R_{A,E} + D_s + D_t + \epsilon_{A,E} . \quad (3)$$

The results from our model parameter estimates are shown in Table 2 along with their standardized (beta coefficient) counterparts.

In addition to the covariates used in the citation impact model, we also included the citation rate to the editor’s articles (f_A , which did not show a significant effect in the citation model, nor would it have a logical mechanism, and hence we excluded it from that model). Consistent with the first model, higher impact articles tend to get accepted more quickly ($\hat{\beta}_z = -0.0343$; $p < 0.000$), as their relative quality may be more easy to identify and accept faster. Also, the more coauthors on the article, the longer the articles tended to take in order to be accepted, in line with expected increasing coordination costs in assembling and submitting referee revisions in large team endeavors ($\hat{\beta}_k = 0.0297$; $p < 0.000$). There was also a significant positive relation between editor service age and the acceptance time, in line with the increasing time demands as an editor becomes busier within the journal compounded by

additional external activities ($\hat{\beta}_\tau = 0.137$; $p < 0.000$).

This model also indicates a negative relation between editor citations and acceptance time ($\beta_f < 0$), albeit the weaker in relative magnitude as indicated by its standardized coefficient ($\hat{\beta}_f = -0.009$; $p < 0.000$). Nevertheless, this significant negative relation again points to an undocumented type of editor bias in the handling of scientific manuscripts, pointing to the remuneration value of a self-citations.

Again, of principal interest is the relation with repeat authors as an indicator of social factors. Indeed, the model indicates a significant reduction in Δ_A for repeat authors ($\beta_R = -0.0878$; $p < 0.000$). In real terms, for the average article, this effect corresponds to roughly a $\langle \Delta_A \rangle (1 - \exp[-0.0878]) = 10$ -day decrease in acceptance time related to $R_{A,E} = 1$ alone. In order to further identify differences in Δ_A arising from vanity incentives, we added an interaction term $f_A \times R_{A,E}$ to the model specified in Eq. 3, in order to distinguish the relation of f between articles with $R = 1$ and $R = 0$. Figure 2(B) captures the marginal effect of f on Δ_A , with articles with $R_{A,E} = 0$ showing a statistically significant negative relation ($\beta_{f \times R=0} = -0.75$; $p < 0.000$, which, if leaning towards a more pessimistic interpretation, would indicate that “*you must pay more the first time.*”

4.4. Unintended incentives associated with Editorial board service

Above all, it is impossible to use the data at hand to know the exact context of each of the references citing PLOS ONE editors’ work. Thus, it is best to assume that the majority of these editor citations follow the same intent purposes of any other citation reference. Nevertheless, motivated by the results of the latter regression model, it is clear that citing the editor – loosely interpretable as an unsolicited remuneration for editorial services – may actually work towards enticing a faster (positive) decision. But to what extent would an editor gain from quietly “playing this market”?

Indeed, in the previous sections, we found evidence that editors may treat repeat authors slightly differently, by lowering their standards of quality judgement and providing faster decision times to the (groups of) authors who an editor repeatedly serves, and possibly has connections to, within the larger academic community. Thus, in this section we seek to estimate the potential net “remuneration” that these repeat authors could effect by citing an editor’s work. Of course, knowledge of the editor’s identity is single-blinded at the point of submission, however it is not impossible that an editor might communicate externally to the authors that he/she is overlooking their manuscript, or that the author’s might informally contact a suspected editor.

To this end, by leveraging the size of the PLOS ONE dataset, we looked for small but measurable differences in the citation rate to editors conditional on the article including or not including repeat authors ($R_{A,E} = 1, 0$, respectively). To be specific, for each editor we collected the set of $N_{E,R=1}$ articles with $R_{A,E} = 1$ and counted the total number of references $C_{R=1}$ and also the number of those references citing the editor’s work, $C_{E,R=1}$. Similarly, for the set of $N_{E,R=0} = N_E - N_{E,R=1}$ articles with $R_{A,E} = 0$, we also calculated $C_{R=0}$ and $C_{E,R=0}$. Thus, the total number of references from all articles overseen by an editor is simply $T_E = C_{R=0} + C_{R=1}$, and the total number of citation received by the editor, independent of R , is $C_E = C_{E,R=1} + C_{E,R=0} = f_E T_E$.

We then define the conditional editor citation rates $f_{E,1} = C_{E,R=1}/C_{R=1}$ and $f_{E,0} = C_{E,R=0}/C_{R=0}$ and plot their distributions $P(f_E|R_{A,E} = 0, 1)$ in Fig. 3(A). The distribution calculated for publications featuring repeat authors ($R = 1$) shows an excess in the extreme right tail, suggesting that these relatively high levels of editor citation rates may correspond to “enticing backscratching”.

In order to further examine signatures of remuneration, we calculated the expected number of citations that an editor might gain due to the differences in citing behavior of repeat versus non-repeat authors. We measure this difference as

$$\Delta C_E = (f_{E,1} - f_{E,0})T_E, \quad (4)$$

which should be equal to 0 for those editors who are completely unbiased with respect to R . Of course, there are fluctuations due to the finite sample size N_E . Figure 3(B) shows the probability distribution $P(\Delta C_E)$ is approximately normally distributed, centered around the mean value $\langle \Delta C_E \rangle = 3.1$ and standard deviation $\sigma_{\Delta C} = 15.4$. However, the distribution deviates from the symmetry of the normal distribution, showing significant right skew (skewness = 3.5) representing the excess number of editors with relatively large and positive number of citations attributable to differences in the citation rates for $R = 1$ versus $R = 0$. Remarkably, we count 39 editors with $\Delta C_E > (\langle \Delta C_E \rangle + 3\sigma_{\Delta C})$, representing 2% of the 1902 editors we analyzed with $N_E \geq 20$; we counted only 2 editors with $\Delta C_E < (\langle \Delta C_E \rangle - 3\sigma_{\Delta C})$.

And finally, Fig. 3(C) combines three editor service measures, editorial power (N_E), longitudinal trends of editorial quality judgement (β_τ), and editorial citation remuneration (C_E) in a single scatter-plot visualization. First, each point, corresponding to an editor, is colored according to the trend in z_A over time. To be specific, we used ordinary least squares regression to estimate the temporal trend in the linear model $z_{A,\tau} = \beta_0 + \beta_\tau \tau$, captured by the coefficient β_τ , using all the articles with $t \leq 2014$ for a single editor. For the editors with significant positive (negative) β_τ (using the significance level $p < 0.1$) we colored their datapoint cyan (orange); we observed 194 editors with a significant positive trend and 100 with a significant negative trend. Remarkably, two top-10 editors – Vladimir Uversky (rank $r = 1$) and Matjaz Perc ($r = 7$) – are distinguished not only by their power and total citation remuneration, but also by the fact that the trends in the citation impact of articles they have accepted has been negative over time ($\beta_\tau < 0$). However, if we eliminate these top two editors (according to N_E) from the orange and cyan subsets, and calculate the power-law relationship between remuneration and editorial service ($C \propto N^\gamma$), we obtain nearly identical fits (shown as solid colored lines) across the entire range of N_E , with approximately equivalent scaling exponent: $\gamma = 0.41$ (orange) and 0.43 (cyan).

5. Summary and discussion

We analyzed the largest journal in the world, focusing on quantifiable measures of editorial power and decision processes. Given its size, the impact that PLOS ONE has on the production of scientific knowledge is high, and given the implicit constraints in monitoring and managing such a large complex system, several of our findings are worrisome, with plausible explanations that range from editorial

apathy to misconduct in their service to science. Thus, our study demonstrates why large megajournals should record, monitor, and embrace transparency, and to make sure the incentives for editor service do not introduce unintended conflicts-of-interest. As science continues to grow, these conflicts-of-interest may become more difficult to avoid, e.g. in large teams or a large journal, because the difficulty in monitor individual activities may foster the conditions for misconduct (Petersen et al., 2014).

By analyzing the entire editorial board comprised of nearly 7,000 editors, we revealed the remarkable levels of inequality in the activity levels among PLOS ONE editors. While the Gini-index equal to 0.58 we calculated for editorial power is remarkably high, it is nevertheless smaller than the Gini index calculated for university funding (Gini index exceeding 0.7) (Xie, 2014) and career achievement (Gini-index for total researcher citations ranging from 0.6 to 0.8) (Petersen and Penner, 2014). A corollary to such power disparity is the additional external power, prestige, and familiarity it may lead to, providing an additional mechanism contributing to cumulative advantage in science (De Solla Price, 1976; Petersen et al., 2011; Petersen and Penner, 2014).

To get a better idea of the power levels among the most prolific editors, we inspected the top-100 editors, ranked according to the total number of articles N_E , and observed a wide range of mean acceptance times among them, ranging from $\Delta_E = 175$ to as short as $\Delta_E = 56$ days, on average. Not surprisingly, and not upstanding, several of the editors with the shortest Δ_E were among the top-10 editors. For example, on average, articles edited by the most active editor, Vladimir Uversky, appear every 3.2 days, a feat which is partly attributable to the relatively short mean article acceptance time $\Delta_E = 77$ days (the editor average is 130 days). The variability in acceptance time within each editor's profile was also high (see Fig. S1A). One potential explanation for the prevalence of such short review times is the portability of external reviews, which can be used in the PLOS ONE editorial decision process (Bjork, 2015).

Assuming that editors have fixed time resources, this power disparity directly translates into a disparity in the time editors (appears to) spend in evaluating each article. The results of our citation model in Section 4.3.1 provide supporting evidence that the quality of his/her service diminishes significantly with higher work-load, as editors' ability to evaluate article quality diminishes significantly over time. While it is clear from this statistical analysis that some editors are overactive, it is important to note that this is not by itself a certain indicator of misconduct. Indeed, short of a case-by-case analysis requiring additional review data, distinguishing good intentions from bad inevitably leads to an in-between gray area where it is difficult to distinguish. Nevertheless, we leveraged the longitudinal aspect of the data using two fixed-effect models to identify trends within editorial profiles.

In the first model, we used the wide range of variation in editor activity as well as longitudinal time to identify factors that can explain the variation article quality – proxied by its citation impact. We used a normalized citation measure to overcome systematic measurement biases that are prevalent in citation analysis. Our results show that editors tend to be biased in favor of authors with whom they have had previous editorial experience. This feature alone is not necessarily unexpected, given the strength of social ties underlying other aspects of the scientific endeavor (Petersen, 2015). However, we found that this effect was pronounced among the top-10 editors. In all, these results of this citation

model are particularly worrisome, showing the ability of editors to evaluate research quality decreases over their editorial career and that editors exhibit bias in favor of repeat authors – a signature of “backscratching” behavioral bias across social ties – which may also be related to poorer quality of the articles accepted.

In the second model, we looked for social factors that might explain the wide variation in acceptance times. We found that articles that have a larger fraction of citations citing the editor’s research were likely to be accepted faster. The most plausible reason that an author might cite the editor’s work is because PLOS ONE editors are acting scientists, and thus central figures within their community. Moreover, as the editor continues to publish him/herself, then clearly he/she has more publications to cite over time. Nevertheless, we found that this new type of “self-citation” (Fowler and Aksnes, 2007; Costas et al., 2010) had a more prominent effect when considering the presence of repeat authors, as captured by the indicator variable $R_{A,E} = 1$ which identifies the articles containing at least one author that published two or more times with that given editor. Figure 2(B) shows a stronger marginal effect of reduced acceptance time when the article does not contain any repeat authors. This effect is related to the literature on self-citations, which offers various plausible explanations in addition to citation rigging, e.g. signaling prestige in cross-disciplinary mobility (Hellsten et al., 2007) as well as bias towards citing one’s past collaborators, to explain the self-citation frequency which ranges between 20 to 40% Costas et al. (2010). Here, however, since the editor has decision power, the incentives to sway that decision are more clear, providing further evidence that directed citations are indeed an effective form of remuneration (Fowler and Aksnes, 2007).

If editor’s are truly privy – and responsive – to such subtle payments, the follow-up question is how much could one really gain by playing this game? Because it is extremely difficult to measure and interpret the context behind individual citations, we appealed to the large data size to look for evidence of variation in editor citation rates (f_E) depending on whether the citations arise from repeat authors or not. Figure 3 provides substantial evidence that a small but significant number of editors may be aware of this game, and our estimates of the total citations attributable to ΔR place a lower bound on this citation remuneration in the hundreds of citations. While editors certainly deserve credit for their service to science, it is important to address the possibility that some editors may have more covert intentions underlying their excess editorial activity.

6. Conclusions

Despite the plethora of researcher metrics being developed and refined in order to evaluate individual scientific achievement (Wilsdon et al., 2015), much less attention has been paid to the scientific actors at the other end of the negotiation table – the editors who serve as scientific gatekeepers. Holding the power to accept or reject a scientific article has obvious ramifications for the authors of the manuscript. Even more, this decision has the profoundly determines whether or not their conclusions enter in to the corpora of scientific literature, and thus, the cannon of scientific knowledge.

As such, it goes without saying that the power that editors hold over the body of scientific knowledge comes also with a lot of responsibility. Maintaining certain levels of quality is crucial for the

advancement of knowledge, which is often incremental, but nevertheless cumulative, building and relying on what has been previously published, and to some extent, what has been legitimized by the scientific review process. By allowing publication standards to diminish, and possibly even disappear, science may become susceptible to incorrect, if not fraudulent, mis-knowledge. With the democratization of online publication in the general sense, it is not implausible that the same prevalence and ease of misinformation spreading in the digital publication world, where the role of editors has been largely diminished or eliminated, could also develop within science. Thus, it is important to highlight the value and responsibility that editors have in maintaining the integrity of science.

We conclude with some editorial policy recommendations. First, especially in the case of megajournals featuring a distributed editor system comprised of acting researchers, we encourage the journals to go beyond the example of PLOS ONE in linking editors to published articles, and to actually record and evaluate editors' activity levels. This is partially a transparency issue, but also a responsibility and sanctioning issue that is necessary for the management of science journals. As gatekeepers to our knowledge base, science editors have a distinct responsibility in remaining unbiased. Our results, however, indicate that social biases are nevertheless predominant features despite best efforts. Second, electronic-only journals which do not have volume restrictions should nevertheless consider placing restrictions on the number of articles an editor can oversee at a time and per year. In addition to discouraging editors from taking advantage of their power, it would also encourage higher quality standards for accepting an article for publication. By implementing such editorial policy changes at PLOS ONE, it would certainly make for an interesting policy experiment, providing an additional opportunity to observe shifts in editorial behavior, and possibly strengthening the case for tying the observed behavioral trends to outright misconduct.

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Table 1: Results of a fixed-effects model for which the dependent variable is the citation impact of an individual article (z_A). Model parameters estimated using editor, year, and subject-area fixed-effects. Only editors with $N_A \geq 10$ articles for the years $t \leq 2014$ are analyzed; see Eq. 2 for the full model specification. Estimates calculated using robust standard errors. The third and fourth columns show estimates including interaction effects.

	Detrended citation impact, z_A							
	Model coefficient		Standardized coeff. ($\hat{\beta}$)		$R \times \ln \tau$		$T_{10} \times R \times \ln \tau$	
$\ln k_A$	0.285***	(0.000)	0.161***	(0.000)	0.286***	(0.000)	0.286***	(0.000)
$\ln \Delta_A$	-0.127***	(0.000)	-0.0755***	(0.000)	-0.127***	(0.000)	-0.127***	(0.000)
$\ln \tau_E$	-0.178***	(0.000)	-0.143***	(0.000)	-0.174***	(0.000)	-0.175***	(0.000)
$R_{A,E}$	0.0895***	(0.000)	0.0895***	(0.000)	0.107***	(0.000)	0.106***	(0.000)
$R_{A,E} \times \ln \tau_E$					-0.0320**	(0.005)	-0.0252*	(0.028)
$T_{10,E} \times \ln \tau_E$							0.0445	(0.433)
$T_{10,E} \times R_{A,E} \times \ln \tau_E$							-0.103*	(0.017)
Constant	-0.813***	(0.000)	-0.970***	(0.000)	-0.823***	(0.000)	-0.818***	(0.000)
Dummy for <i>year</i>	y		y		y		y	
Dummy for <i>SA</i>	y		y		y		y	
N	102741		102741		102741		102741	
adj. R^2	0.035		0.035		0.035		0.035	
F	182.7	(0.000)	182.7	(0.000)	173.4	(0.000)	150.0	(0.000)
df_{model}	16		16		17		20	
$df_{\text{clusters}(E)}$	3084		3084		3084		3084	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Results of a fixed-effects model for which the dependent variable is the logarithm of the acceptance time for an individual article ($\ln \Delta_A$). Model parameters estimated using editor, year, and subject-area fixed-effects. Only editors with $N_A \geq 10$ are analyzed; see Eq. 3 for the full model specification. Estimates calculated using robust standard errors.

	Acceptance time model, $\ln \Delta_A$			
	Model coefficient		Standardized coeff. ($\hat{\beta}$)	
z_A	-0.0343***	(0.000)	-0.0343***	(0.000)
$\ln k_A$	0.0529***	(0.000)	0.0297***	(0.000)
f_A	-0.674***	(0.000)	-0.00895***	(0.000)
$\ln \tau_E$	0.170***	(0.000)	0.137***	(0.000)
$R_{A,E}$	-0.0878***	(0.000)	-0.0878***	(0.000)
constant	3.976***	(0.000)	4.152***	(0.000)
Dummy for <i>year</i>	y		y	
Dummy for <i>SA</i>	y		y	
N	128,734			
adj. R^2	0.064			
F	255.7	(0.000)		
df_{model}	18			
$df_{\text{clusters}(E)}$	3,748			

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

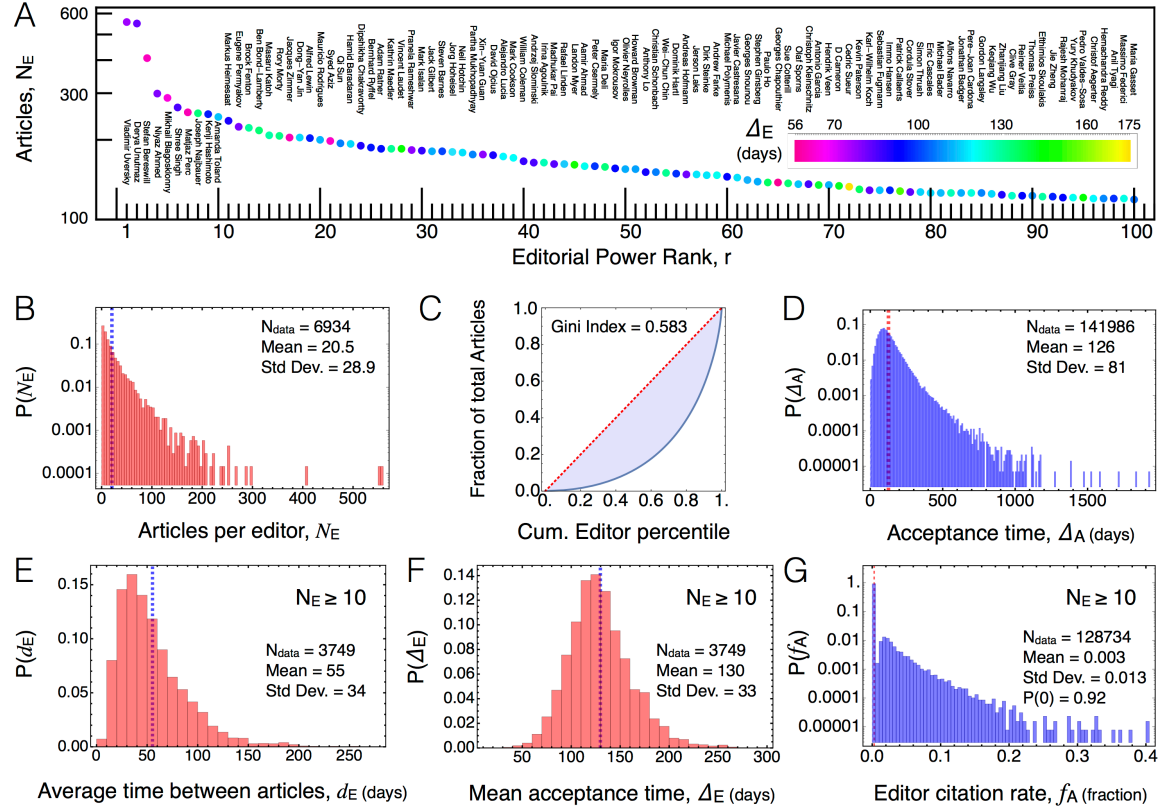


Figure 1: The distribution of editorial power, activity, and citation renunciation at PLOS ONE. (A) The top-100 most active editors ranked according to N_E . Circle color indicates the editor's mean time to acceptance, Δ_E (days); green-yellow values are above the population mean of 130 days (see panel F); blue-magenta values are significantly below the population mean, and are typical of the top-10 editors. (B) The right-skewed distribution of N_E across nearly 7 thousand editors. (C) The Lorenz curve quantifies the cumulative fraction of all articles edited by a given percentile: the bottom 25% of editors oversaw just 3% whereas the the top 10% of editors (693 editors) oversaw 42% of the total 141,986 articles. The Gini-index calculated from the distribution of N_E is 0.583. (D) The distribution of the number of days between an article was received and accepted for publication (i.e. not including the time between acceptance and publication). (E) The distribution of the turnover time (or inverse activity) defined as the average number of days between articles accepted by the same editor. (F) The distribution of the mean number of days to accept an article calculated for each editor; comparable with panel D. (G) The distribution of f_A , the fraction of the references in a given article that cite other papers that include the editor as a coauthor: 92% of papers have $f_A=0$, but there is an extremely long tail. In panels (E-G) we only included data for the 3,749 editors with $N_E \geq 10$ articles in order to reduce the fluctuations due to small sample size; vertical dashed lines indicate distribution mean.

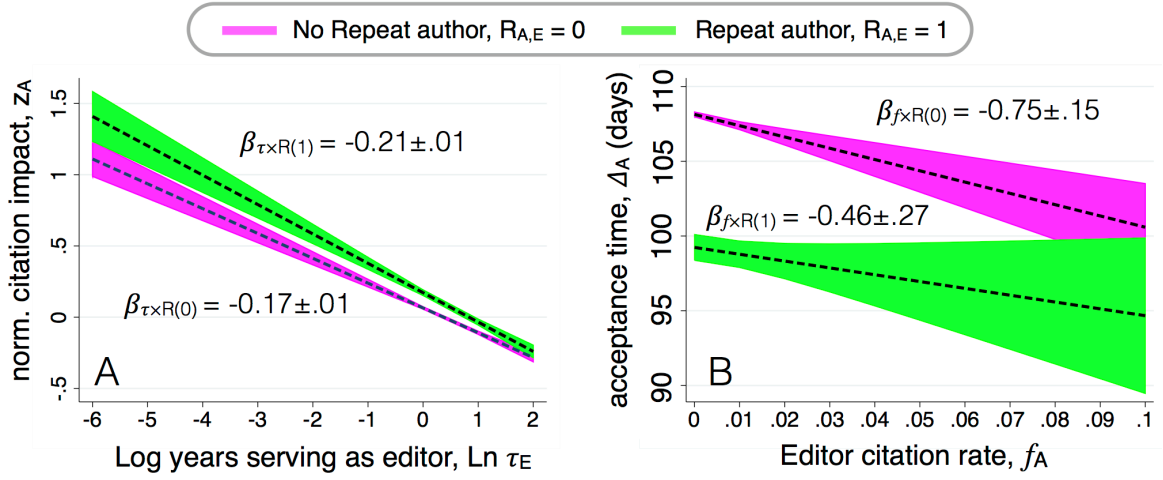


Figure 2: **Quantifying editors' diminishing quality judgment and susceptibility to self-citation.** Shown are linear predictions represented as point estimates with 95% confidence intervals using two fixed-effects models: (A) the normalized citation impact model specified in Eq. 2 and (B) the acceptance-time model specified in Eq. 3. (A) The marginal effect of editorial longevity ($\ln \tau_E$) on the normalized citation impact (z_A) of the articles he/she accepts, including an interaction term $R \times \ln \tau$ to distinguish between those articles with $R = 1$ (with repeat authors) and $R = 0$ (no repeat authors). Both interaction coefficients are negative and significant at the $p < 0.000$ level; the difference in the coefficients is significant at the $p \leq 0.005$ level. (B) The marginal effect of citing the editor's publications (f_A) on the time the editor takes to accept an article Δ_A , including an interaction term $R \times f$ to distinguish between the articles with $R = 1$ and $R = 0$. Both interaction coefficients are negative, however due to small sample size for the $R = 1$ cases, only $\beta_{f \times R(0)}$ ($p < 0.000$) is significant, with $\beta_{f \times R(1)}$ only significant at the $p = 0.096$ level. Shaded interval indicates the 95% confidence interval calculated using the delta method with all covariates evaluated at their mean values.

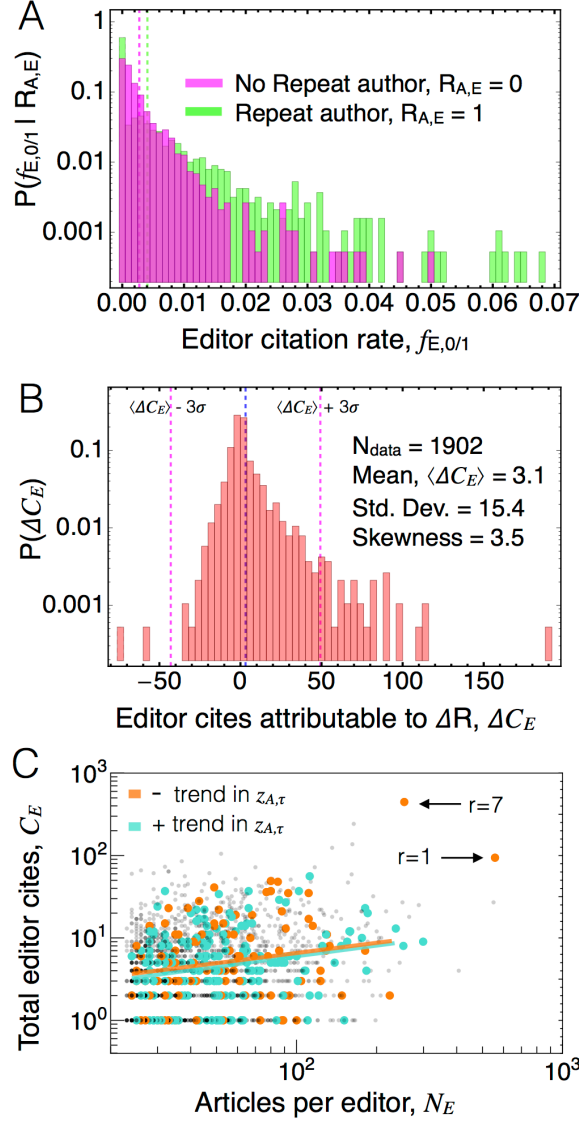


Figure 3: **Estimating the citation renumeration for editorial service.** (A) Conditional citation rate distributions for the articles without any repeat authors $P(f_E|R=0)$ (magenta), and for the articles with repeat authors $P(f_E|R=1)$ (green). The mean values (indicated by the vertical dashed lines) are $\langle f_{E,0} \rangle = 0.0028$ and $\langle f_{E,1} \rangle = 0.0041$. Statistical tests for the difference in means (T-test), difference in median (Mann-Whitney test), and difference in distribution (Kolmogorov-Smirnov test) all reject the null hypothesis that the mean, median, and distributions are equal at the $p < 0.000$ level. (B) Distribution of the excess editor cites due repeat author bias, estimated using the empirical editor-specific difference $\Delta C_E \propto (f_{E,1} - f_{E,0})$ for each author (see Eq. 4). The $\langle \Delta C_E \rangle \pm 3\sigma_{\Delta C}$ confidence intervals are indicated by vertical dashed magenta lines. The asymmetry in the tails of the distribution are evident when considering the outliers, with 39 observations in the right tail and only 2 in the left tail. (C) Scatter plot of editor power (N_E), citation renumeration (C_E) and color indicating the trend in z_A among the articles he/she accepted over time: editors with significant positive (negative) trend in z are colored cyan (orange), and editors with no significant trend (p-value of the regression $p < 0.1$) are colored grey. The two arrows indicate two outliers characterized by high N_E , C_E , and negative trend in z_A , showing their rank identity in Fig 1(A). Solid lines show the regression best-fit between $\log_{10} N_E$ and $\log_{10}(C_E)$, ignoring the two data points with the largest N_E values within each subset; the fits are nearly identical. Each panel is calculated for editors with $N_E \geq 20$.

Supplementary Information

Quantifying the distribution of editorial power and manuscript decision bias at the mega-journal PLOS ONE

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S1. Supplementary Methods

S1.1. Name disambiguation problem among editors and authors

Due to the name disambiguation problem – i.e. it is difficult to distinguish common last name and first name initial combinations in TRWOS data – there are certain abbreviated name combinations that we ignored in aspects of our analysis. First, in order to determine if an article was coauthored by a PLOS ONE editor, there were certain editor names which were too similar in their abbreviated forms, e.g. Shree Singh and Seema Singh, who both occur in TRWOS records as “Singh S”. Thus, for those editor name abbreviations which have a degeneracy of 2 or greater, we do not count articles with these abbreviated names as being coauthored by an editor.

Second, this name disambiguation problem occurs in the identification of the top authors within the article set of each editor. Thus, using the editor name degeneracy set as our baseline, we also ignored all surnames – independent of first name initial – for the common PLOS ONE editor list. As such, the list of common surnames ignored in the coauthor analysis are : Singh, Isalan, Hoheisel, Lo, Castresana, Liu, Zheng, Yang, Deb, Qiu, Chang, Zhou, Bhattacharya, Tang, Lee, Xu, Li, Cheng, Wang, Scott, Yu, Tan, Miao, Williams, Klymkowsky, Kaltenboeck, Zhang, Chen, He, Song, Brown, Lin, Brody, Wei, Kumar, Yan, Shi, Carvalho, Rogers, Ng, Ray, Phillips, Soriano-Mas, Paul, Fox, Butler, Ma, Wu, Carter, Xie, Hector, Wright, Caldwell, Fang, Sorensen, Lam, Chan, Stewart, Huang, Gravenor, Pan, Gupta, Smith, Lu, Cao, Xia, Ho, Moore, Liang, Franco, Parida, Zhao, Wilson, Gilbert, Nigou, Redfield, Paci, Park, Sun, Zhu, Chalmers, Clark, Colombo, Zuo, Das, Tian, Moreno, Meng, Gray, Schweisguth, Lopez-Garcia, Yue, Johnson, Wong, Medina, Fung, Kato, Roberts, Hwang, Hsieh, Wen, Knight, Csernoch, Anderson, Grant, Clarke, Jiang, Jones, Rao, Feng, Nguyen, Choi, Thomas, Chiu, Samuel, Gordon, Heutink, Evans, Martin, Ren, Berger, Kim, Han, Mao, White, McCutcheon, Temussi, Taylor, Schmitt, Kerby, Miller, Roy, Pereira, Shankar, Aoki, Jackson, Adams, Russell, Thompson, Abe, Duan, Hong, Borrás, Costa, Yam, Porollo, Stumbles, Agarwal, Beier, Xiao, Beaudoin, Nosten, Shen, Feldman, Hall, Raible, Yin, Kelly, Simos, Knudsen.

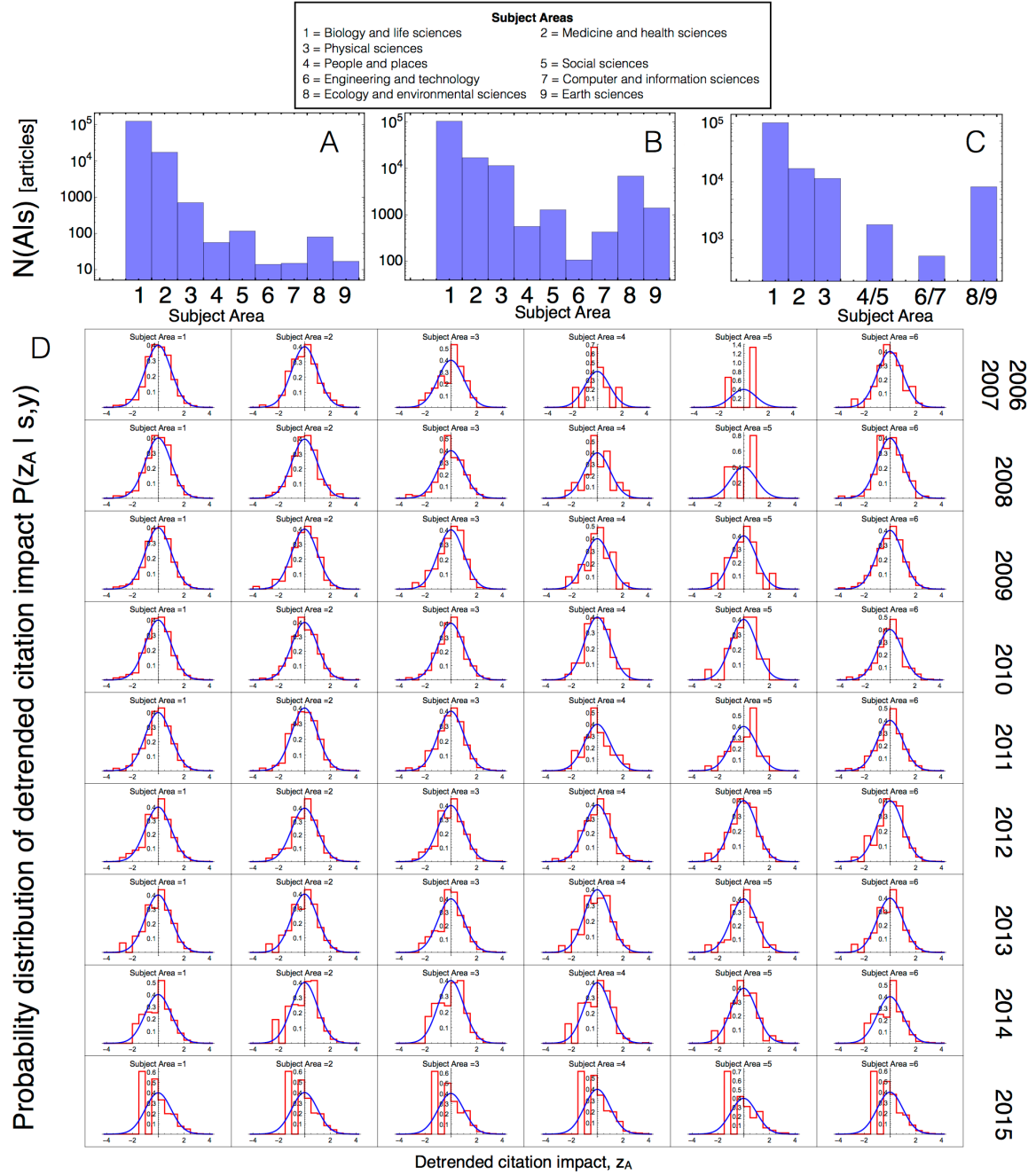


Figure S1: **Distribution of article characteristics: subject area and detrended citation impact.** (A) Count distribution of the number of articles by principal subject area (no articles were observed with “Science policy” as the principle SA). (B) Count distribution by SA after applying redistribution rule that if the principal SA=1, then use the SA with the second-highest weight. (C) Count distribution by SA after merging into 6 refined subject areas, which are used throughout the analysis. (D) Empirical probability distribution $P(z|s, t)$ for each SA and year combination (red bins) and baseline normal distribution $N(0, 1)$ (blue curve) shown to demonstrate the time-independence of the normalized citation impact variable. Since all 2006 articles were published in December, we merged these publications with 2007. The only articles with poor convergence to the $N(0, 1)$ distribution are the relatively recent 2015 articles; these publications are not included in the regression analysis.

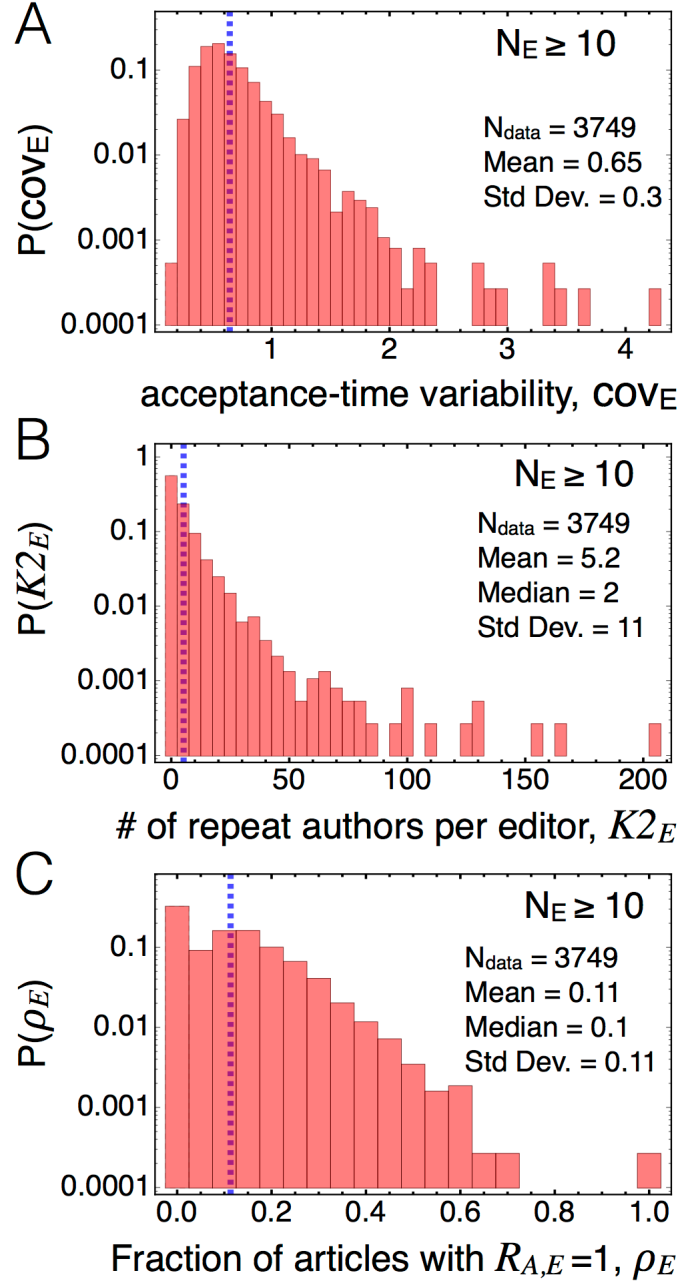


Figure S2: **Editor-level article characteristic distributions.** (A) Probability distribution $P(\text{cov}_E)$ of the variability in Δ_E expressed as the coefficient of variation (the ratio of the standard deviation of Δ_E normalized by the mean Δ_E for a given editor). For most editors the mean Δ_E is rather characteristic, however some editors show a wide range of variability. (B) Probability distribution $P(K2_E)$ of the number $K2_E$ of repeat authors, i.e. the authors that have appeared on 2 or more of the N_E articles within a given editor's article set. (C) Probability distribution $P(\rho_E)$ of the fraction ρ of the total articles of a given editor featuring a repeat author (i.e. fraction of articles with indicator value $R_{A,E} = 1$). In each panel we only analyze editors with $N_E \geq 10$ articles to avoid small sample size fluctuations; vertical dashed lines indicate distribution mean.